Renewable and Sustainable Energy Reviews 23 (2013) 299–311

Contents lists available at SciVerse ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Value chain optimization of forest biomass for bioenergy production: A review

Nazanin Shabani [1], Shaghaygh Akhtari [1], Taraneh Sowlati *

Department of Wood Science, University of British Columbia, 2943-2424 Main Mall, Vancouver, British Columbia, Canada V6T 1Z4

ARTICLE INFO

Article history:
Received 28 November 2012
Received in revised form
20 February 2013
Accepted 2 March 2013
Available online 29 March 2013

Keywords:
Forest bioenergy supply chain
Renewable and sustainable energies
Optimization
Uncertainty

ABSTRACT

Forest biomass is one of the renewable and sustainable sources of energy that can be used for producing electricity, heat, and biofuels. The complex supply chain of forest biomass for energy generation, which consists of different players and products and is affected by biomass characteristics, such as low density and unpredictable quality, makes the energy generation cost from biomass higher than that of the conventional sources of energy, such as fossil fuels. Moreover, variability and uncertainty in this supply chain, mainly due to the nature of material, economic condition and market fluctuation, affect the amount of produced energy and its cost. Mathematical modeling, in particular optimization techniques, can be employed to manage the supply chain and achieve the optimum design. This paper reviews studies which used deterministic and stochastic mathematical models to optimize forest biomass supply chains for electricity, heat and biofuels production. Optimization models were used to provide the optimum solution for decisions related to the network design, technology choice, plant size and location, storage location, mix of products and raw materials, logistics options, supply areas, and material flows. Mainly, economic objectives were considered in these models. Further studies should consider environmental and social objectives, in addition to the economic ones, in the models. In non-deterministic models uncertainty mainly in the demand, supply, prices, and conversion yields were incorporated. Although material quality is an important uncertain parameter in the forest biomass supply chain that affects the amount and cost of produced energy, its variation was not considered in previous studies.

Contents

1. Introduction

Increasing the contribution of biomass in energy generation is considered as an important step in developing sustainable communities and managing greenhouse gas emissions effectively [1]. Although the conversion and transportation of forest biomass for

* Corresponding author. Tel.: +1 604 822 6109.
E-mail addresses: nshabani@interchange.ubc.ca (N. Shabani), akhtari.shaghayegh@gmail.com (S. Akhtari), taraneh.sowlati@ubc.ca (T. Sowlati).
[1] Tel.: +1 604 8274583.

1364-0321/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.rser.2013.03.005

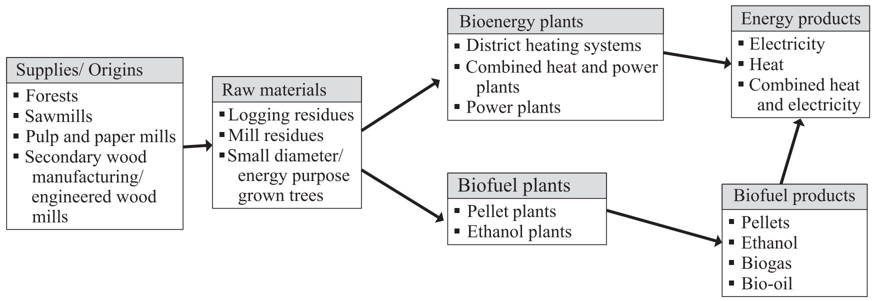

Fig. 1. Forest biomass supply chain for energy production.

energy generation affect the air quality negatively [2], energy generation from forest biomass has the potential to decrease carbon emissions significantly when it substitutes fossil fuels [3–6]. Converting forest biomass to energy also has the potential to recover the waste that would otherwise be disposed to landfills or be incinerated, create jobs, provide local and sustainable energy for communities, and decrease their dependency on the international fuel market. Compared to other renewable energy sources such as wind or solar, the advantage of using forest biomass for energy generation is that it can be stored and used on demand [2,7].

Despite these advantages, there are several barriers in utilizing forest biomass as an energy source. One challenge is the complexity of forest bioenergy supply chains which is partly resulted from complexity in forest industries supply chain in general. Forest industries consist of different interrelated and interconnected sectors, products and markets [8]. As an example, the raw material of the bioenergy facilities can be supplied from final products or by-products of some other plants such as sawmills, and pulp and paper mills. Therefore, the economic situation and the production mix of these plants can directly impact the raw material availability and its quality for bioenergy production. Moreover, unlike fossil fuels, forest biomass is usually speared over large areas rather than being concentrated. Also, forest biomass is a bulky material with relatively low density (400 and 900 kg/m^3 [7]), and high moisture content [3]. These characteristics contribute to high cost and complexity of forest biomass supply logistics [7]. The transportation cost could account for 50% of the total delivery cost of biomass in some cases [9] and the logistics system could comprise large number of equipment pieces and different transportation modes [2]. It is usually needed to convert forest fuel into chips before delivering it to the customer [10]. Inaccessibility of forests in some months during the year, when energy demand is quite high, raises concerns about the secure supply of biomass to energy plants. Therefore, storage, which affects the quality of material [11], is also important in this supply chain. Comminuting and storing residues can be done either in the forest, at the plant or at an intermediate point. The location of an energy plant also plays a key role in the economic performance of energy generation from forest biomass. There is variability and uncertainty in forest bioenergy supply chains due to several other factors, such as market instability, natural disasters, and policy and climate changes as well as the nature of the industry (for example heterogeneous raw material and unpredictable quality [3]). Uncertainty makes this supply chain volatile and risk vulnerable, which in turn makes the proper planning difficult. All these challenges contribute to high cost of forest bioenergy compared to other sources of energy. Utilizing more advanced technologies, for example to improve raw material quality or system efficiency, is one way to deal with some of these challenges. Another solution for improving the performance of a forest bioenergy supply chain is to optimize its design and management.

Mathematical programming models can be used to optimize these supply chains. These models are effective particularly when different parts of the supply chain, such as procurement, production, transportation, and distribution, and different decision levels, such as strategic, tactical and operational levels, are integrated. Usually, decisions regarding the supply chain design such as location, technology and capacity are made in the strategic level, while decisions related to the flow of material and production planning can be made in tactical and operational levels.

Optimization techniques have been employed for modeling supply chains in different industries including forest industries [8]. In addition to modeling the supply chain, optimization has the advantage of providing the optimum solution based on the objective function (s) defined in the model. Using optimization techniques in designing and management of forest bioenergy supply chain can result in better performance which helps making this energy source economically viable [12]. In several previous studies, optimization techniques have been employed to manage the forest bioenergy supply chain for heat, electricity and biofuels production from strategic, tactical and operational point of views. Most of these studies were deterministic and ignored uncertainty, while there are examples that included uncertainty in the supply chain models especially during the past few years. This paper reviews all of these studies.

A number of papers reviewed the literature related to different parts of the bioenergy supply chain. Jebaraj and Iniyan [13] reviewed energy models and allocated a small section of renewable energies in their paper to biomass and a section to optimization models in energy systems in general. Baños et al. [14] reviewed studies that used optimization methods in renewable and sustainable energies and dedicated a section to the bioenergy industry. These studies were not comprehensive and only provided examples from the bioenergy supply chain. Wang et al. [15] and Scott et al. [16] reviewed the multi-criteria decision making methods applied in sustainable energy decision-making and bioenergy systems, respectively. These studies did not focus on optimization and supply chain design and management problems. Johnson et al. [17] studied methods and literature on optimum location of forest biomass–biofuel facilities and did not consider other decisions in the supply chain. The potential application of geographic information system (GIS) in evaluating the feasibility of bioenergy projects was studied by Calvert [18]. As noted by the author, geographical aspects are important factors affecting the feasibility of such projects. The use of spatial data and GIS in modeling of the value chains could be helpful in location analysis, transportation cost estimation, and actual (vs. potential) feedstock availability quantification. Awudu and Zhang [19] reviewed studies that considered uncertainty in biofuel supply chains. The authors only focused on the biofuel industry and did not include deterministic cases or those related to heat and energy plants. Moreover, they considered both agricultural biomass and forest biomass which have different origin and different supply chains. The present paper is more comprehensive compared to the above

mentioned review papers since it covers previous studies on optimization of forest bioenergy supply chain design and management, including those for heat, electricity and biofuels production. It also discusses the issue of uncertainty in these supply chains, its sources and the methods used for dealing with it. This paper gives a comprehensive review on the deterministic and stochastic models used for forest bioenergy supply chain in literature. The studies are categorized in two groups: (1) studies that used deterministic mathematical programming for modeling biomass supply chain in generating heat and/or electricity (mostly in district energy systems) and biofuels, and (2) studies that incorporated uncertainty in their modeling of forest bioenergy supply chain. The main focus of the reviewed studies was on optimizing the supply chain profit, while other objectives related to environmental and social issues should be considered in future studies.

2. Deterministic optimization models

The wood flow in the forest products supply chain starts from harvest areas to value added mills such as sawmills, pulp and paper mills, secondary wood products, wood pellet mills, and eventually bioenergy plants [8]. These mills produce different products, and may generate co-products (demand-driven) or by-products (secondary results of production). Forest biomass for the purpose of energy generation can be supplied from forest residues including branches and tops left in the harvest areas, by-products of other forest product mills, such as sawdust, bark and shavings [7], and fast growing crops such as poplar and willow grown specifically for energy purposes [20]. Chipping, handling, transporting, storing and pre-processing operations, such as drying for improving the quality of biomass, are usually needed before using the forest biomass for energy generation. The energy production process depends on the conversion technology used in the energy plant [21]. Forest biomass can be used for energy generation either directly, such as in direct heat and power generation, or indirectly such as in biofuels (pellet, bioethanol) production. The energy generation technologies include pelletization, combustion, co-combustion, gasification, pyrolysis, digestion and fermentation [7,22]. Different types of energy products are then sent to customers through the grid, networks or channels of distributors, wholesalers and retailers. Profit in each stage of the forest bioenergy supply chain is a function of procurement, transportation, operating, capital and other costs, and depends also on the availability and quality of biomass [23]. Fig. 1 shows the network of generating energy from forest biomass.

Different optimization techniques, such as linear programming (LP) and mixed integer linear programming (MILP), have been used for supply chain design and management. LP is a mathematical method which includes a set of variables to be determined, a linear objective function to be optimized, and a set of linear equality or inequality constraints to be met. The main advantages of using this optimization method are the ability of LP algorithm to solve large scale problems, its assured convergence to global optimum solutions, having no need to have an initial solution and its use of a well-developed duality theory for sensitivity analysis and the ease of problem formulation. If some of the variables in LP are integer, the model is called mixed integer linear programming (MILP). In this section, the studies that used optimization in supply chain design and management of district heating systems, electricity plants, biofuel plants and co-generation plants that utilize forest biomass are reviewed.

2.1. District heating plants

One of the main uses of forest biomass for energy generation is in district heating systems. In a district heating system (DHS), a central plant generates thermal energy and a network of pipelines distributes the produced energy in the form of hot water or steam to a group of customers in a community [24,25]. Heat exchangers installed at each building draw off the heat from water and when heat has been circulated within the interior atmosphere, a separate pipe network returns the water to the central plant for reheating [26]. In addition to heat and hot water, district energy systems may provide chilled water.

District heating systems became popular after the oil crisis in the 1970s because of their high efficiency in energy generation [26] compared to decentralized systems, which produce and consume energy within the same building. As a consequence of higher efficiency, primary fuel consumption decreases and some negative environmental impacts of burning fuels might be offset. District heating systems can use a wide variety of fuels including fossil fuels and renewables and offer better pollution control than decentralized systems [27].

Some studies have shown that the costs of using biomass for energy generation in district energy plants are higher than other sources of energy such as fossil fuels [28–32]. While this fact may seem to be discouraging for making investments in biomass district heating projects, it is notable to consider that forest biomass utilization for power and thermal energy generation has environmental, social, and economic benefits in some cases. Governmental subsides and grants could help these plants to be competitive with other sources as was the case in Sweden, a pioneer country in exploiting forest biomass in energy plants [33]. The effect of biomass price and/or subsidies on the profitability and structure of heating plant supply chains have been studied and discussed in [34–37].

The cost of energy generation in a district heating plant is related to the delivery cost of biomass, location of plants, the type of technology that is used to convert biomass into a useful from of energy and the operating scale of energy generation plants. The cost advantage of larger systems, known as economy of scale, is a known fact. However, larger systems require more forest fuel and consequently more raw material which result in having higher transportation costs. A significant cost factor in energy generation from forest biomass is the conversion technology cost. Purchase price, installation, pre-treatment, operating and maintenance, and labor costs differ for various types of technical solutions. Furthermore, conversion technologies are different in terms of efficiency which dictates the amount of required biomass and affects the transportation cost.

Choosing the conversion technology is one of the strategic decisions that may be made in the design of a heating plant supply chain. For example, decisions can be made to select between a co-generation system and an individual system [34], or select among different technologies, such as grate firing combustion (GFC), fluidized bed combustion (FBC), fluidized bed gasification (FBG), and fast pyrolysis (FP) [22]. In [34], the investment cost, fixed and variable costs, fuel cost, waste disposal cost and revenue from selling energy (heat and/or electricity) were the components of the objective function of a mixed integer programming model. In [22], a linear programming optimization model was developed for each individual technology and the optimum values of their objective functions were compared. The authors concluded that despite the low efficiency of grate firing combustion, it was the best technology to be adopted because of its lower installation and management costs compared to other alternative technologies. The same authors then changed their model to mixed integer programming to find the optimal conversion technology with only one run of model using binary variables in the model [38].

Usually, an optimization model can be used to make decisions about different variables, such as size and location of the plant, material flow, etc. at the same time. Chinese et al. [35] used a

Table 1
Summary of studies on deterministic optimization of forest biomass district heating plant supply chains.

Author	Year—region	Objective function	Decision variables	Method
Eriksson et al. [39]	1989—Sweden	Minimizing supply cost of forest biomass (chipping, storing and transportation costs)	Flow of biomass direct or via storage Chipping location	Linear Programming (LP)
Nagel [34]	2000—Germany	Maximizing annual profit (revenue from sale of energy minus investment cost, fixed and variable costs, fuel cost and waste disposal cost)	Level of heat produced by each boiler at each time period The capacity of the system Whether or not to integrate a boiler into the heating system (Binary variable)	Mixed Integer Programming (MIP)
Gunnarsson et al. [40]	2004—Sweden	Minimizing biomass supply cost (transportation, chipping and storage costs)	Flow of biomass within the supply network Quantity of biomass chipped and stored at roadside and terminal If biomass is forwarded to or is chipped at each roadside location (Binary variable) If each sawmill is contracted or not (Binary variable) If each terminal is used or not (Binary variable)	Mixed Integer Programming (MIP)
Chinese et al. [35]	2005—Italy	Maximizing annual profit (revenues from sale of thermal energy and charging customers with connection fees minus boiler investment cost and construction and operating costs of facility)	Heat produced by each boiler at each time period The capacity of the system If a boiler would integrate to the heating system or not (Binary variable)	Mixed Integer Programming (MIP)
Frombo et al. [22]	2009—Italy	Maximizing net annual profit (revenue from sale of heat and power minus felling and processing, skidding, highway transportation, plant installation and management costs)	Annual quantity of biomass harvested from each supply area The plant capacity for different conversion technologies	Linear Programming (LP)
Frombo et al. [38]	2009—Italy	Maximizing net annual profit (revenue from sale of heat and power minus felling and processing, skidding, highway transportation, plant installation and management costs)	The quantity of biomass harvested at each harvesting location and to be used at each plant location The capacity of each plant Selection of the conversion technology (Binary variables)	Mixed Integer Programming (MIP)
Kanzian et al. [42]	2009—Austria	Minimizing biomass supply cost to the heating plants (chipping, storing and transporting costs)	Volume of wood chips transported from each terminal to each plant Location of terminals and plants (Binary variable)	Mixed Linear Programming (MIP)
Van Dykenetal. [43]	2010—Norway	Minimizing the present value of the costs (investment and operating costs and salvage value)	Biomass and product flow within the supply network Energy flow within the supply network Emissions from storing and drying biomass Biomass input and output moisture content to and from dryer Biomass storage duration (Binary variable)	Linear and Mixed Integer Programming (LP and MIP)
Keirstead et al. [41]	2012—UK	Minimizing system cost (biomass purchase, storage, transportation and conversion costs)	Optimal capacity of boilers Whether chipped forest biomass should be imported from neighbor area or non-chipped residues should be imported and then chipped within the area (Binary variable)	Mixed Integer Programming (MIP)
Han and Murphy [44]	2012—US	Minimize the weighted sum of transportation costs Minimize the total working time	Truck schedules	Simulated annealing

mixed integer model to obtain the most profitable configuration of a multi-source biomass district heating plant including decisions about the optimal size of the plant, resources to be integrated to the network and the sequence of integrating boilers to the network under different government subsidy levels. The energy sources consisted of the exhausted steam from an existing district electricity generation turbine, along with wood wastes from local manufacturers. Five individual biomass-fired boilers with different capacities were identified to provide process heat for this industrial district. Virtual boilers including a new natural gas boiler and a new woody biomass boiler were also considered.

Finding the optimal flow of biomass from buffer storages to energy plants while minimizing the supply cost has been of great interest in the available literature. At the tactical level, one of the premier studies which used mathematical programming in the operation of a district heating system was done by Eriksson and Björheden [39]. They developed a model to make the following decisions: whether to transport biomass to the heating plant directly or via storage, and whether to chip biomass at roadside or at the plant. The results of the optimal solutions were to chip residues at the roadside and direct flow of chips to the heating plant. When storage was used, additional transportation cost incurred and the authors showed that this additional transportation cost would not be paid off by the improved quality (better moisture content) of biomass after storage. A more complex situation where several storages and heating plants are included in the supply chain could be dealt with decision support systems (DSS) as was implemented in [40]. The objective of this mixed integer based DSS was to minimize the supply cost of biomass to heating plants including forwarding, chipping, storing and transportation costs. The DSS defined the optimal location for chipping forest residues, and an optimal monthly plan for flow of wood chips from roadside to the storages and plants, from storages to heating plants, and also from sawmills to the storages and plants. The mixed integer programming model in a study [41] found the optimum cost of forest biomass supply for fulfilling the heat demand of an urban area. This optimization model was used to decide between importing wood chips and forest residues from nearby area. When the decision was to import forest residue, the chipping process was carried out within the studied area. The objective function in this study was to minimize the annual cost including annual fuel, biomass storage, transportation, and conversion costs. A supply chain of 16 combined heat and power plants and 8 terminal storages with a total capacity of 178,250 m^3 in Austria were studied in [42]. The authors presented an optimization model to minimize the biomass supply cost to the plants, which included chipping, storing, and transporting costs, while defining the optimal flow of wood chips. The results of this study were similar to those in [39], which indicated direct flow of biomass was less expensive than indirect flow via terminal.

Van Dyken et al. [43] developed a linear mixed-integer model for biomass supply chain with transport, storage and processing operations at the operational level. In their case study, they considered 12 weekly time steps and three different biomass products including spruce, wood chips and wood pellets. There were constant weekly demands for both wood chips and heat. The demand for wood chips was fulfilled partly from chip supply and partly from chipping spruce in a chipper with an additional cost. To improve the biomass quality, two kinds of drying were considered: active drying through dryer and passive drying through storage. Active drying increased the cost and emissions since it consumed energy, while passive drying caused volume loss. After drying, part of chips was used to fulfill biomass demand and the rest was sent to the second storage which followed into a pellet mill and a heating plant. The optimization model was solved and the optimum operational plan, which minimized the total cost including the fuel cost, biomass cost and electricity cost, was derived for the case study.

A truck scheduling optimization problem was studied in [44] for transporting forest biomass from harvesting sites and sawmills to heating plants, pulp plants or export harbors in Oregon, US. The problem contained four types of forest biomass including hog fuel, chips, sawdust, and shavings transported from 45 sawmills to 20 conversion facilities over a 1 year period using 75 chip vans and an average of 100 truckloads per day. The objective function was to minimize the weighted sum of transportation costs and the total working time. Different constraints were included in the model such as routes, working time and predetermined order requirements. A heuristic algorithm, called simulated annealing, was used for solving this optimization problem. The author indicated that this algorithm provides "near optimal" solution which was still better than the existing situation in terms of transportation cost and total travel time (18% and 15% lower, respectively).

Table 1 summarizes the studies discussed in this section.

2.2. Power plants

Forest biomass can be used in power plants for generating electricity. It can be burnt at a constant rate in a boiler furnace to heat water and produce steam. Then, the steam is carried through the furnace using pipes to raise its temperature and pressure further. Finally, the steam passes through the multiple blades of a turbine, spinning the shaft and the shaft runs an electricity generator which produces an alternating current to use locally or to supply the national grid [7].

The optimal supply area and location of a forest biomass power plant in a distributed power generation system was determined by Reche et al. [45]. The objective function was to maximize the profitability index as a function of the net present value of benefits from the sale of electrical energy minus the initial investment, collection, transportation, maintenance and operating costs. The authors used an artificial intelligence method, called particle swarm optimization. They concluded it is important in distributed generation systems to consider the technical constraints of the network and the voltage regulation. Finally, they evaluated the model performance using simulation.

Alam et al. [46] constructed a three-objective model for optimizing the amount of each individual type of biomass from each of the harvesting zones, and then applied their model to a 50 MW h biomass power plant using both harvesting residues and poplar trees collected from three management zones in Northwestern Ontario, Canada. To optimize the supply chain of energy plants, it is sometimes necessary to formulate a problem with more than one objective since single objective models cannot always represent the problem accurately. The objectives are often in conflict (minimizing and maximizing objectives) and it might not be possible to achieve an optimal solution that optimizes all the objectives simultaneously. In this situation, the trade-off between objectives can be shown and the most efficient solution is selected. In [46], pre-emptive goal programming was applied to give priorities to the objectives as follows: (1) minimizing the procurement cost of feedstock, (2) minimizing the transportation distance of biomass supply to the plant, and (3) minimizing the feedstock moisture content.

Finding the optimal size, location, supply area and net present value of an electricity plant in Spain was studied in [47]. The raw material of the power plant was olive tree pruning residues and the technology for electricity generation was gasifier with gas turbine. The authors used GIS data for the location and number of olive trees per kilometer square, roads, topographical features, electric lines location, etc. Different plant sizes and locations were considered and the optimal one with the highest net present value was determined using three metaheuristic methods. These methods were Genetic Algorithms (GA), Binary Honey Bee Foraging (BHBF) and Binary Particle Swarm Optimization (BPSO). It was

Table 2
Summary of studies on deterministic optimization of forest biomass power plant supply chains.

Author	Year—region	Objective function	Decision variables	Method
Reche et al. [45]	2008—Spain	Maximizing profitability index (net present value of revenue from selling electricity minus initial investment, biomass collection and transportation costs, and maintenance and operation costs)	Location and supply area of the biomass power plant	Particle swarm optimization
Alam et al. [46]	2010—Canada	Minimizing total biomass procurement cost Minimizing total distance for procurement of biomass Maximizing the quality of biomass (minimizing moisture content)	Quantity of biomass procured from each supply location to each plant Biomass procurement zone selection (Binary variable)	Multi-objective Programming
Vera et al. [47]	2010—Spain	Maximizing net present value (revenue from the sale of electrical energy minus initial investment and collection, transportation, maintenance and operation costs)	Pant size and location Supply area	Several metaheuristic methods
Shabani and Sowlati [48]	2013—Canada	Maximize the profit (revenue from selling electricity minus procurement, transportation, production, storage and ash management costs)	How much biomass to purchase, store and consume in each month Whether or not to produce surplus electricity (binary)	Mixed Integer Programming (MIP)

Table 3
Summary of studies on deterministic optimization of forest biomass biofuel plant supply chains.

Author	Year—region	Objective function	Decision variables	Method
Chinese et al. [51]	2009—Italy	Minimizing total cost of supply chain (harvesting, transportation, processing and facility installation costs)	Flow of biomass within the supply network Whether to use a pre-processing equipment, e.g. dryer, or not (Binary variable)	Mixed Integer Programming (MIP)
Ekşioğlu et al. [52]	2009—USA	Minimizing total annual cost (investment, harvesting, storing and transportation costs)	Number, size, and location of bio- refineries required Quantity of biomass harvested, shipped, processed and stored Whether a biorefinery and a collection facility with specific size are located in each site (Binary variables)	Mixed Integer Programming (MIP)
Santibañez et al. [53]	2011—Mexico	Maximizing profit (revenue from sale of products minus investment, process, operating and transportation costs) Minimizing environmental impacts	The quantity of products produced from different biomass feedstock using different processing routes The quantity of each biomass feedstock used for producing different products through different processing routes	Multi-objective Programming

concluded that BHBF algorithm converged to the optimal solution better than BPSO and GA. The results indicated that the optimal plant size was 2 MW and the predicted optimal location of the plant was in the area with highest available biomass.

In a recent study, the value chain of a forest biomass power plant was optimized [48]. The authors included forest biomass procurement, storage, production and ash management in a dynamic model consisted of a 1-year plan with monthly time steps. The objective function was to maximize the power plant's profit, while meeting the constraints related to production capacity, maximum available supply, demand fulfillment, material flow balance and storage limits considering biomass quality, in terms of moisture content and higher heating value, in the optimization model. The problem was solved using a mixed integer non-linear model and was applied to a real case study. Different scenarios on biomass availability and investment in a new ash recovery system were considered. It was concluded that investment in a new ash recovery system had economic and environmental benefits for the power plant. The sensitivity analysis results showed that variations in some parameters, such as maximum available biomass, electricity price, biomass price and quality, had higher impact than other parameters on the optimum solution.

Table 2 summarizes the studies using optimization models in forest biomass power plant supply chains.

2.3. Biofuel plants

The bioethanol production has increased in recent years in many countries, such as US. Although most of the bioethanol is produced from agricultural biomass, the controversial issue of using plants as fuel instead of food made it necessary to look for more acceptable sources, namely forest biomass [49]. Generating biofuels from forest biomass is still in the developing phase and has not been commercialized yet. The main challenges in commercialization of this technology include high energy consumption for woody biomass pretreatment, even when compared to agricultural biomass, low system efficiency, process scalability and intensive capital investment [50]. In most of the studies presented here, forest biomass combined with agricultural biomass is used for biofuel production.

Chinese et al. [51] considered a real-life problem of supplying a biofuel plant with forest fuel. A mixed-integer linear programming model was proposed to determine the optimal configuration of the supply chain. It was mentioned that the model could be useful in resolving trade-offs between decentralized early treatment of biofuels, resulting in lower transportation costs, and centralized final treatment, allowing to reap the benefits of economies of scale. It was therefore advised to apply integrated supply chain planning concepts to design biofuel logistics systems and to support policy making in the energy field. An MIP model was also developed by Ekşioğlu et al. [52] for designing the bio-refinery supply chain producing cellulosic ethanol from agricultural and woody biomass. The model outputs were the number, size and location of bio-refinery plants with the objective of minimizing the total cost of annual harvesting, storing, transporting and processing biomass; storing and transporting ethanol; and locating and operating bio-refineries. The model included constraints on biomass availability, flow, conversion, production and inventory capacities, and demand. The data from the State of Mississippi was used to validate the model. The author concluded that transportation costs, biomass availability, technology type, and planting and

harvesting costs are important factors in supply chain design decisions.

The trade-off between economic and environmental objectives in the optimal planning of a bio-refinery in Mexico was evaluated in [53]. The authors used a multi-objective optimization model for selecting the feedstock type, processing technology, and a set of products in a bio-refinery supply chain. The raw material contained different types of agricultural biomass, wood chips, sawdust, commercial wood for producing ethanol, hydrogen, and biodiesel (generated only from agricultural biomass). The objectives were (1) to maximize the profit considering the costs of feedstock, products, and processing, and (2) to minimize the life cycle environmental impacts. The authors applied their model to a case study in Mexico. The decision makers could select from the output the solutions that fit the specific requirements and compensate for both objectives simultaneously.

Table 3 summarizes the optimization studies in forest biofuel plant supply chains.

2.4. Co-generation plants

Combined heat and power (CHP) systems are another type of energy plants that use co-generation technology to produce both heat and power in a district heating system [25]. CHP systems have up to 35–40% higher efficiency than conventional power generation systems [27]. In some studies, mathematical programming was used to compare the cost of generating either energy or biofuels from biomass and also to evaluate the possibility of co-generation.

Some studies indicated that utilizing biomass for energy generation is more cost efficient than for biofuel production. Azar et al. [54] proved that utilizing biomass in the heat sector was the most economical scenario. Wahlund et al. [55] showed that using wood biomass for pelletization would have a lower cost and higher CO_2 reduction than using it for biofuel production. Feng et al. [56] investigated the possibility of having bioenergy facilities (they called it biorefinery) in typical existing sawmills, pulp and paper mills, wood panel facilities, biochemical, energy, and pellet facilities. Then, the authors developed a mathematical model to design this integrated supply chain optimally.

A methodology for optimizing the utilization of distributed biomass resources for energy production was proposed by Alfonso et al. [57]. The main focus of the paper was to optimize the logistics, but economic and environmental analyses of different bioenergy alternatives were also performed. The authors indicated that the methodology would provide the optimal locations of the biomass plant, energy application (electricity, heat and/or standardized biofuels such as pellets), and the employed technology. This methodology was applied to three districts in Spain. Based on the results, the authors concluded that the shortest payback period and highest CO_2 savings were attained from co-generation plants, followed by pellet plants. The least ranked option was power-only power plants.

Difs et al. [36] analyzed different biomass gasification scenarios, and determined the optimum configuration with the current fossil fuel price and green energy policies. Wetterlund and Söderström [58] considered two scenarios of co-generating Synthetic Natural Gas (SNG) and district heat, and co-generation of heat and power. The authors determined the policy support levels (tradable biofuel certificates) that would make the SNG scenario cost competitive with CHP, while maximizing the annual profit over a 20-year time period. They concluded that no financial support would be required for combined heat and power generation because the market price of electricity was high enough.

The cost-effectiveness of different applications of biomass gasification was analyzed by Börjesson and Ahlgren [37]. The focus of this study was to determine whether CHP generation in biomass integrated gasification combined cycle (BIGCC) plants, and biofuels production in biomass gasification biorefineries in a case study in Sweden were cost efficient. Examples of the model outputs included electricity production, use of electricity, biofuels production, required biofuel subsidy level, CO2 emissions, and total use of biomass. The authors indicated that the outcome of their model was not an optimized system because the systems they studied consisted of a number of subsystems, each controlled by different actors with probably a bigger interest of optimizing their own subsystem than the overall system. They mentioned that the results were rather an illustration of what could be than a prediction of the future development.

Schmidt et al. [59] used a mixed integer linear programming model for optimizing the location of bioenergy plants using forest biomass in Austria. The bioenergy plants included integrated gasification combined cycle (IGCC) system and biomass CHP plants with carbon capture storage (CCS), pellet mill, and transportation fuel (methanol and ethanol) plants. The optimal size of the plant and biomass allocation area for different systems were also considered. It was found that the production of transportation fuels were not economical.

The problem of indicating whether to produce electricity in addition to heat at biomass combustion plants was studied by Freppaz et al. [60]. Their model's objective function was to maximize the financial yield of six proposed plants, while deciding about the annual amount of biomass harvested in each collection area, the annual flow of biomass from each collection area to each plant, the percentages of heat and electricity generated in each plant and the capacity of combustion system in each plant.

A decision support system (DSS) was presented by Rentizelas et al. [61] to optimize a multi-biomass energy conversion system to generate electricity, heating and cooling in an area in Greece. The objective function was to maximize the financial yield of the investment, while meeting customer demand. The decision variables included the location and size of the bioenergy facility, the biomass types and quantities and the maximum collection distance for each type. The authors concluded that considering multi-biomass supply chain reduced the cost by decreasing warehousing requirements, especially for seasonal types of biomass. The developed model was non-linear and a hybrid optimization method was used to solve that.

Rauch and Gronalt [62] developed a model for designing a forest fuel CHP plant supply chain in Austria by making decisions about transportation modes and spatial arrangement of terminals. The model was a mixed integer programming model with the objective function of minimizing the total procurement cost. The effect of changes in forest fuel supply (domestic resources or imports), transport modes (truck only, truck and ship, or truck, ship and rail), energy price (increase by 0%, 20% and 40%), and truck load capacity (50%, 40% and 30%) on the overall cost was evaluated. Eight scenarios were constructed and compared. Table 1 shows the summary of studies discussed above.

The summary of studies on optimization of forest biomass co-generation plant supply chains is provided in Table 4.

3. Uncertainty in the forest biomass supply chains

Uncertainty is referred to lack of information or lack of degree of belief in the validity of the information about the existing or future state of a system [63]. Uncertainty can result from measurement errors and ignorance, which is to some extent inevitable and might be reduced by further studies or investing in improved technology to acquire high quality data [64,65]. Uncertainty may result from variability in random future events due to their

Table 4
Summary of studies on deterministic optimization of forest biomass co-generation plant supply chains.

Author	Year—region	Objective function	Decision variables	Method
Freppaz et al. [60]	2004—Italy	Maximizing annual profit (revenues from sale of energy minus harvesting, transportation, installation and maintenance, and energy distribution costs)	Annual quantity of biomass harvested at each collection area and transported from each collection area to each of six district energy systems Capacity of each plant The percentage of thermal energy generated at each plants If the plant produces electricity or not (Binary variable)	Mixed Integer Programming (MIP)
Alfonso et al. [57]	2009—Spain	Minimize transport duration, optimize the location, etc.	Biomass resources, logistics structure, bioenergy plants size and location, technology type, etc.	Did not mention
Rentizelas et al. [61]	2009—Greece	Maximizing the financial yield of the investment	Location and size of the bioenergy facility The biomass types and quantities The maximum collection distance for each type	Hybrid optimization
Börjesson et al. [37]	2010—Sweden	Not discussed in the paper	The optimal production capacity at different subsidy levels Selection of alternative technologies for district heat generation (Binary variable)	Mixed Integer Programming (MIP)
Difs et al. [36]	2010—Sweden	Maximizing annual profit (revenues from sale of energy products minus investment, fuel and maintenance costs)	Capacity of new investment Selection of investment alternatives for future (Binary variable)	Mixed Integer Programming (MIP)
Schmidt et al. [59]	2010—Austria	Minimizing total cost of energy generation (biomass supply and transportation costs, bioenergy generation cost, carbon capture and storage cost, plant building and distribution network investment costs, and distribution cost)	The annual amount of energy commodities produced at plants: heat, power, pellets, and transportation fuels Plant size and location (Binary variable) Pipeline networks selection (Binary variable) District heating networks selection (Binary variable)	Mixed Integer Programming (MIP)
Wetterlund and Söderström [58]	2010—Sweden	Maximizing annual profit (revenues from sale of electricity and synthetic natural gas minus investment, fuel and maintenance costs)	The optimal government support level (subsidy) Selection of new investment alternatives (Binary variable)	Mixed Integer Programming (MIP)
Rauch and Gronalt [62]	2011—Austria	Minimizing total procurement cost (transport, chipping investment, operations and maintenance costs)	The annual volume of fuel transported between districts, terminals, regional departure railway, and the CHP plant Open or close a terminal (Binary variable)	Mixed Integer Programming (MIP)

inherent nature (such as feedstock characteristics) [66], which can be controlled to some extend by employing better forecasting methods and/or using expert judgment. It can also result from lack of reliable historical data or lack of certainty in historical data, for example lack of data on the demand of a new product. Other sources of uncertainty include imprecision in judgment, vagueness, and ambiguity related to the known objects, which belong to poorly defined sets so they cannot be classified well [63–65]. This form of uncertainty is secondary as it may be the consequence of a lack of control in the manufacturing system, which can be decreased using some technologies such as part-tracking systems.

From the system boundary point of view, the source of uncertainty may exist outside the production process, called environmental uncertainty, such as uncertainty in demand and supply, or it may be within the production process, called system uncertainty, such as uncertainty in lead time due to machine failure [67].

In terms of time horizon, uncertainty may be the result of short term variations, such as day-to-day processing variations, canceled/rushed orders and equipment failure, or long-term variations, such as raw material/final product unit price fluctuations, seasonal demand variations and technology changes. Therefore, uncertainty exists in supply chains at strategic, tactical and operational levels and should be considered in supply chain decisions.

While some of the sources of uncertainty in forest biomass supply chains are similar to other industries, such as economic fluctuation and instability, raw material supplies, manufacturing process time, machine breakdown, reliability of transportation channels, and exchange rates, there are other sources of uncertainty that are related to the specific characteristics of forest biomass supply chains which are summarized here.

Interdependency between different forest sectors: There are interdependencies between different sectors and markets within the forest industry supply chains. Consequently, variations in one part of the supply chain usually propagate into the other parts. For instance, the downfall of the economy and the US housing market collapse in 2007 resulted in the closure of many Canadian sawmills in 2008 [68]. This impact was not limited to the lumber industry and resulted in the decrease of residual chip supplies for pulp and paper mills, bioenergy power plants and other wood chip users. Some bioenergy power plants had to curtail their operation for several months due to the shortage of supply.

Changing feedstock supply: The need for having a continuous supply of raw material for a bioenergy facility necessitates the use of a mixture of material or even to have new material sources in the future. Therefore, this industry has a dynamic supply chain over time which may have significant variations, such as variations in its environmental impacts [66].

Wood is a heterogeneous natural material: Its physical and chemical characteristics affect products quality and quantity [66]. In bioenergy industry, the moisture content and heating value of raw material play an important role in the amount of produced energy and its costs [6]. Heating value and moisture content vary from one tree stands or species to another [7,69,70] and also differs in different types of biomass (e.g. bark, sawdust, shavings) [71]. Wood properties may be affected by external factors, such as growth condition, climate, harvesting methods, storage and transportation methods. Biomass quality, such as moisture content, can also change during storage, production, and transportation.

Divergent production structure: Forest products industries generally have a divergent production structure, which means multiple products, by-products, and co-products are made from a single product simultaneously. Consequently, it is difficult to completely control the manufacturing processes. Moreover, it is challenging to forecast the quality and quantity of outputs due to this production structure and the use of heterogeneous natural raw material in the production. This fact can impact the amount of raw material available for bioenergy plants, which are supplied from other forest product mills.

Ambiguous values and objectives: Most forest areas include large areas with diverse geographical and ecological characteristics. In forestry, it is usually needed to incorporate different values and stakeholders' preferences and interests which sometimes cannot be understood, interpreted and quantified completely [65]. Therefore, it is likely to have vague factors, values and objectives which can also exist in the forest bioenergy supply chain. This aspect of uncertainty cannot be dealt with like other sources of uncertainty. To some extent, it is possible to spend time and money in some forms of consulting with the stakeholders to get a better understanding of their preferences, opinions, and values. However, sometimes the stakeholders may not be able to express their preferences before a specific decision is made. The studies considering this type of uncertainty are not in the scope of this review paper.

New markets and new production technologies: Recently, there has been an increased attention to utilizing forest biomass for bioenergy and biomaterials production. Investment grants, carbon and energy taxes, green certificate schemes, conversion technologies, and availability and quality of biomass resources may not be known with certainty [72]. For example, in designing and planning a biomass power plant, it may be hard to estimate the long term availability, quality and cost of biomass. Alternatively, market demand for biofuels may not be lucid from the beginning.

In general, uncertainty can be dealt with at the source, or it can be dealt with during the process of decision making. When uncertainty is ignored, the decision making is based on the expected values of stochastic parameters, which may be different from their actual values and may lead to non-optimal or infeasible results and solutions. Considering uncertainty in decision making usually helps companies safeguard against threats on one hand and take advantage of the opportunities that higher levels of uncertainty would provide on the other hand. It also makes decisions robust and mitigates the effect of the variations on the optimal solution.

3.1. Modeling approaches

In the literature, several approaches were used to incorporate uncertainty in the supply chain design and management including scenario-based approaches, sensitivity analysis, stochastic optimization, and robust optimization. Mula et al. [73] provided an overview of the uncertainty in production planning. Based on their classification, the supply chain planning and management problems with uncertainty are usually solved by conceptual, analytical or artificial intelligent based approaches. Some of the methods for dealing with uncertainty are out of the scope of this paper since they were not employed in forest biomass/bioenergy supply chain studies, such as fuzzy sets and fuzzy logic [74], expert systems, reinforcement learning, neural networks, genetic algorithms and multi-agent systems [73].

Often times, stochastic models are difficult to solve computationally. In many studies, a simple approach is taken by replacing the random variables by their expected values. In other words, in these studies the developed model is implemented for a single future “scenario”. Another simplified method is to generate different scenarios for future and solve the model for each scenario one at a time and then combine these different solutions by some heuristic rules. Scenario generation itself is a challenging task which can be done using historical data, forecasting methods, managerial and expert judgment, etc. [75,76]. The scenario-based approach provides an extensive what-if analysis which helps in

evaluating the outcomes based on different scenarios of the stochastic parameters. A set of optimal values attained from this method can be used for extracting expected value and standard deviation of the objective function and decision variables. However, it may not determine the optimal solution for some realization of uncertain parameters or there might be a possibility to have a better overall optimal solution. Another issue with this approach is that the likelihood of occurrence of each scenario has a great effect on the optimal solution, but it cannot be determined with certainty.

The analytical approaches (or stochastic models) are usually based on mathematical programming and optimization methods. In stochastic modeling, also called recourse programs, it is assumed that accurate probabilistic descriptions of the random variables such as probability distributions, densities or other probability measures are available. Details of stochastic and recourse modeling can be found in [75]. In these methods, decision variables are divided into two groups called the first stage variables (control, here-and-now), which are made before the realization of the uncertain parameters, and the second stage variables (state, wait-and-see), which are taken after the realization of the uncertain variables. The output of such a model is the optimal single first-stage policy and a set of recourse decision rules determining which second-stage action should be taken in response to each random variable. Often, some decomposition methods such as the Bender decomposition are used in the recourse modeling to accelerate the achievement of the optimal solutions [77]. One of the advantages of developing stochastic programming models is in their capability to manage risk associated with the company's performance.

Another approach for incorporating uncertainty in supply chain management and planning problems is called robust optimization. This method is used when ranges of random variables are known. In this method, a function called “protection function” is formulated for each constraint containing uncertain parameters. The protection function is an optimization problem in itself which determines the size of buffer required to immunize a constraint against uncertainty based on degree of uncertainty of the parameters and degree of the desired protection. After formulation of the protection function and transforming it to an optimization model, its linear version of the dual model is obtained and embedded into the original model. The resulted model, called the robust counterpart, is larger but still linear and can be solved by LP solver packages [78].

In summary, sensitivity analysis is very useful in determining the sensitive uncertain parameters, those parameters that even a small change in them would affect the solution. Then, models considering variations only in the sensitive parameters, instead of all the uncertain parameters, could be developed. The scenario analysis technique, which is a highly effective and easy to understand approach, can be used to deal with uncertainty. In this method, a series of cases that represent the possible input parameters are considered independently. The solution (output) for each scenario is determined separately and compared with the solution of other scenarios based on a performance measure to make the required decision. When the set of scenarios is large, a Monte Carlo simulation can help in generating additional statistical information for the solution, such as average, frequency, bounds, etc. Stochastic programming also considers a set of scenarios, however, unlike scenario analysis, it considers all of the scenarios at once with each scenario at a certain probability and finds a solution that is feasible for all scenarios. When the range of uncertain parameter is known, not its distribution, then the robust optimization method can be employed. Fixed minimum and maximum ranges for uncertain inputs are usually used in this method. Robust optimization models can be solved efficiently as the size of the problem grows slightly when uncertainty is added. Moreover, it is suitable for cases where scenarios or distribution functions cannot be defined and only a range for uncertain parameter can be acquired.

3.2. Previous studies

There are few studies which considered uncertainty in the forest biomass supply chain and all are reviewed here. One study which used sensitivity analysis in the forest biomass supply chain was conducted by Kim et al. [79]. They developed a mixed integer linear programming optimization model for the supply chain design of bio-gasoline and biodiesel production from six forestry resources (logging residuals, thinnings, prunings, inter-cropped grasses, and chips/shavings). The first set of conversion plants could be from a set of candidate sites with four capacity options to convert biomass to three product types: bio-oil, char and fuel gas. These intermediate products could be used either as local fuel sources or as feedstock to produce final products (gasoline and biodiesel) at the second conversion plants, which could be from a set of candidate sites with four capacity options. There were several possible markets for the final products with certain maximum demands. The objective of the model was to maximize the overall profit by determining the number, location, and size of the conversion plants, biomass supply locations, the logistics and the amount of materials to be transported between the various nodes of the designed network, while satisfying the demand constraints. The considered case study was based on an industrial database related to a case in the Southeastern United States. The authors evaluated the trade-off between centralized and distributed network designs. They also run their model for different demands (100% to 90%, 75% and 60%) to evaluate the effect of changes in demand on the optimal network design. The results showed the total profit for the distributed system was higher than that for the centralized design at 100% demand. When the demand decreased, the profit difference between the two systems reduced as well. In this study, although demand uncertainty was evaluated through a very simple sensitivity analysis method, it showed the importance of considering uncertainty as it affected the optimal result.

Kim et al. [80] performed a global sensitivity analysis and two-stage stochastic programming on a biofuel supply chain model and evaluated the effect of uncertainty in different parameters on the final result using Monte-Carlo simulation. The uncertain parameters included availability and acquisition cost of each biomass type, annualized capital cost of two conversion processing plants, cost of transporting intermediate products, biomass and final products, value of each intermediate product at the first conversion processing site, yield of intermediate products from biomass at the first conversion processing, yield of final products from intermediate products at the second conversion processing, maximum demand, operating costs for two conversion processing plants, and the price of each final product. The authors concluded that the most important uncertain parameters affecting the profit were the price of the final product, the conversion yield ratios of the two conversion processes, maximum demand and biomass availability. They then generated 33 scenarios from changing these five most important uncertain parameters by $\pm 20\%$ and developed an optimal model to maximize the expected profit from all these scenarios plus the expected value scenario. The first stage decision variables were the size and location of the processing plants and the second stage recourse decision variables were flows of biomass and product within plants and markets. They implemented the robustness analysis and Monte Carlo global sensitivity analysis to compare the performance of the multiple scenario design with the single scenario design. It was concluded the impact of variations in

stochastic parameters on the optimal solution was mitigated in the model that optimized multiple scenarios. In this paper, uncertain parameters were only changed within some range rather than using probability distributions. Moreover, it only modeled the supply chain in one time-step and ignored the possibility of having correlation between random parameters.

Strategic decisions regarding choosing investment options for heat savings and decreasing energy imports or increasing energy exports in pulp mills under market uncertainty was studied in [81]. The objective function of the developed model was to maximize the expected net present value of the investments. The decision variables were related to investment in heat savings and energy conversion technologies as well as distribution of the obtained heat from different energy conversion technologies. The uncertainty was considered in future energy prices and policy instruments through a scenario tree of five different combinations of several emission reduction policies, and electricity, lignin and bark prices. The original optimization model was a mixed-binary linear programming model and uncertainty was included using a multistage stochastic programming model. Each stage contained 5 years and the total planning horizon was assumed to be 30 years. In [82], Svensson and Berntsson introduced a methodology for making decisions about investment in new energy technologies in industrial plants. The main focus of the paper was to include uncertainty in the energy market. The authors used stochastic programming and scenario analysis to take into account the uncertainty in CO_2 charge, and crude oil and electricity prices. They then applied the methodology to a pulp mill and presented examples of possible future investments to show the usefulness of the proposed approach.

Chen and Fan [83] developed a mixed integer stochastic programming model to incorporate uncertainty in strategic planning of bioenergy supply chain systems. They considered bioethanol production, feedstock procurement, and fuel delivery in an integrated model to minimize costs. The raw material included both agricultural and forest biomass. A two-stage stochastic programming model was developed and applied to a case study in California. Uncertainty was considered in available feedstock supply and fuel demand. A Lagrangian relaxation based decomposition solution algorithm, called progressive hedging method, was used to reduce the computational effort needed to solve the stochastic model. This method decomposed a stochastic problem across scenarios by partitioning the original problem into manageable sub-problems. The first stage decision variables were refinery and terminal locations and sizes and the second stage decision variables were feedstock procurement and transportation, ethanol production and transportation. In the baseline scenario, four discrete demand scenarios with equal probabilities were considered and the results showed that the stochastic programming provided lower expected and more reliable (within smaller range) total system cost than deterministic solutions. In the second scenario, uncertainty in biomass supply was considered using ten scenarios of feedstock with equal probabilities and a fixed demand. The authors stated that the optimal solution of the bioethanol supply chain was not sensitive to the uncertainty in supply. This study did not integrate different sources of uncertainty within a single framework. It also ignored uncertainty in production yields and prices. In addition, the model had single annual time-step and did not consider multiple shorter time variations.

One of the by-products of the Kraft process in the pulp and paper industry is black liquor, which can also be used for energy production. Tay et al. [84] considered uncertainties in raw material supply and product demand in integrated biorefineries using the robust optimization method. The model was mixed integer non-linear programming with one time step. Different scenarios with associated probabilities were considered for supply and product demand. The results identified the optimum capacity of each process technology and its corresponding amount of biomass, intermediate and final products.

Table 5 summarizes the previous studies which incorporated uncertainty in the forest biomass supply chain management and design.

The studies reviewed here indicated the benefits and advantages of incorporating uncertainty in the decision making over developing deterministic models only.Generally, there are several challenges in designing and solving a model with uncertainty which have prevented its wide spread applications. First, these mathematical models are usually complex. Second, considering uncertainty in the models usually requires more time and solving them requires more computational effort compared to the deterministic cases. When uncertainty is considered in several parameters, the size of the problem might become too large to be solved. Another challenge is the difficulty in quantifying uncertainty in mathematical terms. In case of stochastic models, estimating the probability distributions of each random parameter and the probability of occurrence of each scenario are not straightforward and may have great impact on the final solution. If some random variables are correlated, the estimation of their probability is even more difficult. Statistical data analysis and forecasting methods which may be based on the historical data along with managerial judgment could be used in estimating such probabilities. Generating adequate finite scenarios for modeling an uncertain environment with infinite possible outcome (in case of continues variables) is another challenge.

4. Conclusions

Energy generation from forest fuel has several advantages, most importantly in terms of mitigating adverse environmental impacts of fossil fuels. It helps societies diversify their energy sources by providing local energy for communities and

Table 5
Summary of studies on optimization of forest bioenergy supply chain with uncertainty.

Author	Year	Uncertain parameter	Method	Case study
Kim et al. [79]	2010	Demand	Sensitivity analysis	Biofuel industry in Southeastern United States
Kim et al. [80]	2011	Price of the final product, the conversion yield ratios of the two conversion processes, maximum demand and biomass availability	Two-stage stochastic programming	Biofuel industry in Southeastern United States
Svensson et al. [81]	2011	Emission reduction policies, electricity, lignin and bark prices	Multi-stage stochastic programming	Pulp industry in Sweden
Svensson et al. [82]	2011	CO_2 charge, fuel and electricity prices	Multi-stage stochastic programming	Pulp industry in Sweden
Chen and Fan [83]	2012	Feedstock supply and demand	Two-stage stochastic programming with decomposition	Biofuel industry in California
Tay et al. [84]	2012	Raw material supply and product demand	Robust optimization	Kraft pulp and paper industry

potentially sell bioenergy products in the energy market. Commercialization of this energy source, however, is still under consideration. Characteristics of the forest biomass supply chain for energy production, such as unpredicted raw material quality and costly transportation, make it among expensive energy sources in the market. Optimization of forest biomass supply chains could help in commercializing this sustainable energy source by reducing costs.

Mathematical programming and optimization techniques were used in the design and management of forest biomass supply chains. These models were used to provide the optimum solution for decisions related to the network design, technology choice, plant size and location, storage location, mix of products and raw materials, logistics options, supply areas, and material flows. The objective functions included profit/cost, CO_2 emissions, travel time, etc. Both deterministic and stochastic mathematical programming models were developed for forest biomass supply chains.

As environmental and social impacts of products and processes are becoming more important than the pure economic value, future studies using deterministic modeling should incorporate environmental and social objectives in addition to the economic objective into the models and perform multi-objective optimization. Considering non-economic objectives into the models would help deal with important issues, such as carbon emissions, land use, communities' interests, job creation, governmental policies, ecological impacts of removing residues from forest areas, and recreational aspects of forests, and provide possible trade-offs between different objectives.

Deterministic models are necessary and helpful but not enough for capturing all aspects of forest biomass supply chains. Most of the parameters and events in forest biomass supply chains, such as wood quality, market situation, prices, and yields, are uncertain. Uncertainty makes this industry volatile and the long term planning difficult. Even in the short term, variations in raw material quality can impact the performance and efficiency of forest bioenergy production. Despite the interest and much effort in extending deterministic models, only a number of previous studies considered uncertainty in optimizing forest bioenergy supply chains. Understanding the problem characteristics, gathering sufficient data and choosing the appropriate methodology are important in developing stochastic models in forest biomass supply chains. The appropriate methods to be implemented depend on the characteristics of the problem, data availability and form, and type of uncertainties.

In the literature, sensitivity analysis and stochastic programming approach were used to deal with uncertainties in supply, demand, prices, conversion yields, carbon tax and emission reduction policies in forest biomass supply chains. None of the previous studies dealt with uncertainty in biomass quality, such as moisture content and heating value, and its effect on the produced energy and its costs, especially transportation costs. It is worthy to integrate different forest supply chains due to their dependency and model the whole value chain considering harvest areas, sawmills, pulp mills, and bioenergy conversion facilities, and evaluate the effect of uncertainty in one chain on the supply, production and demand of the chains. This, however, would make the modeling and solution approach more complicated. Correlation between uncertain parameters is another interesting topic which has been overlooked in the design and management of forest biomass supply chains.

Acknowledgment

The authors would like to thank the Natural Sciences and Engineering Council of Canada (NSERC) for providing the funding for this research.

References

[1] Ragauskas AJ, Williams CK, Davison BH, Britovsek G, Cairney J, Eckert CA, et al. The path forward for biofuels and biomaterials. Science 2006;311 (5760):484–9.
[2] Hall DO, Scrase JI. Will biomass be the environmentally friendly fuel of the future? Biomass and Bioenergy 1998;15(4–5):357–67.
[3] Hall JP. Sustainable production of forest biomass for energy. Forestry Chronicle 2002;78(3):391–6.
[4] Ahtikoski A, Heikkilä J, Alenius V, Siren M. Economic viability of utilizing biomass energy from young stands—the case of Finland. Biomass and Bioenergy 2008;32(11):988–96.
[5] International Energy Agency (IEA). CO_2 emissions from fuel combustion. 2011; Available from: ⟨http://www.iea.org/co2highlights/co2highlights.pdf⟩.
[6] Saidur R, Abdelaziz EA, Demirbas A, Hossain MS, Mekhilef S. A review on biomass as a fuel for boilers. Renewable and Sustainable Energy Reviews 2011;15(5):2262–89.
[7] Demirbaş A. Biomass resource facilities and biomass conversion processing for fuels and chemicals. Energy Conversion and Management 2001;42 (11):1357–78.
[8] D'Amours S, Rönnqvist M, Weintraub. Using operational research for supply chain planning in the forest product industry. Information Systems and Operational Research 2008;46(4):265–81.
[9] Allen J, Browne M, Hunter A, Boyd J, Palmer H. Logistics management and costs of biomass fuel supply. International Journal of Physical Distribution & Logistics Management 1998;28(6):463–77.
[10] Flisberg P, Frisk M, Ronnqvist M. FuelOpt: a decision support system for forest fuel logistics. Journal of Operational Research Society 2012;63 (11):1600–12.
[11] Fuller WS. Chip pile storage—a review of practices to avoid detoriation and economic losses. Tappi Journal 1985;68:48–52.
[12] Bowyer JL, Shmulsky R, Haygreen JG. Forest products and wood science: an introduction. 5th ed. Ames, Iowa, USA:Blackwell Publishing; 2007.
[13] Jebaraj S, Iniyan S. A review of energy models. Renewable and Sustainable Energy Reviews 2006;10(4):281–311.
[14] Baños R, Manzano-Agugliaro F, Montoya FG, Gil C, Alcayde A, Gómez J. Optimization methods applied to renewable and sustainable energy: a review. Renewable and Sustainable Energy Reviews 2011;15(4):1753–66.
[15] Wang J, Jing Y, Zhang C, Zhao J. Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renewable and Sustainable Energy Reviews 2009;13(9):2263–78.
[16] Scott JA, Ho W, Dey PK. A review of multi-criteria decision-making methods for bioenergy systems. Energy 2012;42(1):146–56.
[17] Johnson DM, Jenkins TL, Zhang F. Methods for optimally locating a forest biomass-to-biofuel facility. Biofuels 2012;3(4):489–503.
[18] Calvert K. Geomatics and bioenergy feasibility assessments: taking stock and looking forward. Renewable and Sustainable Energy Reviews 2011;15 (2):1117–24.
[19] Awudu I, Zhang J. Uncertainties and sustainability concepts in biofuel supply chain management: a review. Renewable and Sustainable Energy Reviews 2012;16(2):1359–68.
[20] Rockwood DL, Naidu CV, Carter DR, Rahmani M, Spriggs TA, Lin C, et al. Short-rotation woody crops and phytoremediation: opportunities for agroforestry? Agroforestry Systems 2004;61–62(1–3):51–63.
[21] Rentizelas AA, Tolis AJ, Tatsiopoulos IP. Logistics issues of biomass: the storage problem and the multi-biomass supply chain. Renewable and Sustainable Energy Reviews 2009;13(4):887–94.
[22] Frombo F, Minciardi R, Robba M, Rosso F, Sacile R. Planning woody biomass logistics for energy production: a strategic decision model. Biomass Bioenergy 2009;33(3):372–83.
[23] Gunn EA. Some perspectives on strategic forest management models and the forest products supply chain. Information Systems and Operational Research 2009;47(3):261–72.
[24] CDE, Canadian District Energy Association. District energy a national survey report; 2009.
[25] Gilmour B, Warren J. Advancing district energy development in Canada: a process for site selection. Review and Community Participation 2007.
[26] Schweig G. Feasibility of wood fuelled district heating in a remote community. University of Toronto; 1997.
[27] Gochenour C. District energy trends, issues, and opportunities: the role of the World Bank. World Bank Publications; 2001.
[28] Walsh ME, Becker D, Graham R, Lichtenberg E. Estimated government savings from biomass production on CRP acres. Energy Crops Forum Oak Ridge National Laboratory, Tennessee, USA, 1995.
[29] Schneider B, Kaltschmitt M. Heat supply from woody biomass—an economic analysis. Ecological Engineering 2000;16(Suppl. 1, 0):123–35.
[30] van den Broek R, Teeuwisse S, Healion K, Kent T, van Wijk A, Faaij A, et al. Potentials for electricity production from wood in Ireland. Energy 2001;26 (11):991–1013.
[31] Gan J, Smith CT. A comparative analysis of woody biomass and coal for electricity generation under various CO_2 emission reductions and taxes. Biomass Bioenergy 2006;30(4):296–303.
[32] Ghafghazi S, Sowlati T, Sokhansanj S, Melin S. Techno-economic analysis of renewable energy source options for a district heating project. International Journal of Energy Research 2010;34:1109–20.

[33] Löfstedt RE. The use of biomass energy in a regional context: the case of Växjö Energi, Sweden. Biomass Bioenergy 1996;11(1):33–42.
[34] Nagel J. Determination of an economic energy supply structure based on biomass using a mixed-integer linear optimization model. Ecological Engineering 2000;16(Suppl. 1, 0):91–102.
[35] Chinese D, Meneghetti A. Optimisation models for decision support in the development of biomass-based industrial district-heating networks in Italy. Applied Energy 2005;82(3):228–54.
[36] Difs K, Wetterlund E, Trygg L, Söderström M. Biomass gasification opportunities in a district heating system. Biomass Bioenergy 2010;34(5):637–51.
[37] Börjesson M, Ahlgren EO. Biomass gasification in cost-optimized district heating systems—a regional modelling analysis. Energy Policy 2010;38(1):168–80.
[38] Frombo F, Minciardi R, Robba M, Sacile R. A decision support system for planning biomass-based energy production. Energy 2009;34(3):362–9.
[39] Eriksson LO, Björheden R. Optimal storing, transport and processing for a forest-fuel supplier. European Journal of Operational Research 1989;43(1):26–33.
[40] Gunnarsson H, Rönnqvist M, Lundgren JT. Supply chain modelling of forest fuel. European Journal of Operational Research 2004;158(1):103–23.
[41] Keirstead J, Samsatli N, Pantaleo AM, Shah N. Evaluating biomass energy strategies for a UK eco-town with an MILP optimization model. Biomass Bioenergy 2012;39(0):306–16.
[42] Kanzian C, Holzleitner F, Stampfer K, Ashton S. Regional energy wood logistics—optimizing local fuel supply. Silva Fennica 2009;43(1):113–28.
[43] Van Dyken S, Bakken BH, Skjelbred HI. Linear mixed-integer models for biomass supply chains with transport, storage and processing. Energy 2010;35(3):1338–50.
[44] Han S, Murphy GE. Solving a woody biomass truck scheduling problem for a transport company in Western Oregon, USA. Biomass Bioenergy 2012;44(0):47–55.
[45] Reche López P, Jurado F, Ruiz Reyes N, García Galán S, Gómez M. Particle swarm optimization for biomass-fuelled systems with technical constraints. Engineering Applications of Artificial Intelligence 2008;21(8):1389–96.
[46] Alam Md B., Shah C., Pulkki R, Wood Biomass Supply Model for Bioenergy Production in Northwestern Ontario. In: Proceedings of 1st international conference on the developments in renewable energy technology (ICDRET); 2009.
[47] Vera D, Carabias J, Jurado F, Ruiz-Reyes NA. Honey Bee Foraging approach for optimal location of a biomass power plant. Applied Energy 2010;87(7):2119–27.
[48] Shabani N, Sowlati T. A mixed integer non-linear programming model for tactical value chain optimization of a wood biomass power plant. Applied Energy 2013;104:353–61.
[49] Limayem A, Ricke SC. Lignocellulosic biomass for bioethanol production: current perspectives, potential issues and future prospects. Progress in Energy and Combustion 2012;38(4):449–67.
[50] Zhu JY, Pan XJ. Woody biomass pretreatment for cellulosic ethanol production: technology and energy consumption evaluation. Bioresource Technology 2010;101(13):4992–5002.
[51] Chinese D, Meneghetti A. Design of forest biofuel supply chains. International Journal of Logistics Systems and Management 2009;5(5):525–50.
[52] Ekşioğlu SD, Acharya A, Leightley LE, Arora S. Analyzing the design and management of biomass-to-biorefinery supply chain. Computers & Industrial Engineering 2009;57(4):1342–52.
[53] Santibañez-Aguilar JE, González-Campos JB, Ponce-Ortega JM, Serna-González M, El-Halwagi MM. Optimal planning of a biomass conversion system considering economic and environmental aspects. Industrial & Engineering Chemistry Research 2011;50(14):8558–70.
[54] Azar C, Lindgren K, Andersson BA. Global energy scenarios meeting stringent CO_2 constraints—cost-effective fuel choices in the transportation sector. Energy Policy 2003;31(10):961–76.
[55] Wahlund B, Yan J, Westermark M. Increasing biomass utilisation in energy systems: a comparative study of CO_2 reduction and cost for different bioenergy processing options. Biomass Bioenergy 2004;26(6):531–44.
[56] Feng Y, D'Amours S, Lebel L., Nourelfath M. Integrated bio-refinery and forest products supply chain network design using mathematical programming approach. 2010; Available from: 〈https://www.cirrelt.ca/DocumentsTravail/CIRRELT-2010-50.pdf〉.
[57] Alfonso D, Perpiñá C, Pérez-Navarro A, Peñalvo E, Vargas C, Cárdenas R. Methodology for optimization of distributed biomass resources evaluation, management and final energy use. Biomass Bioenergy 2009;33(8):1070–9.
[58] Wetterlund E, Söderström M. Biomass gasification in district heating systems—the effect of economic energy policies. Applied Energy 2010;87(9):2914–22.
[59] Schmidt J, Leduc S, Dotzauer E, Kindermann G, Schmid E. Cost-effective CO_2 emission reduction through heat, power and biofuel production from woody biomass: A spatially explicit comparison of conversion technologies. Applied Energy 2010;87(7):2128–41.
[60] Freppaz D, Minciardi R, Robba M, Rovatti M, Sacile R, Taramasso A. Optimizing forest biomass exploitation for energy supply at a regional level. Biomass Bioenergy 2004;26(1):15–25.
[61] Rentizelas AA, Tatsiopoulos IP, Tolis A. An optimization model for multi-biomass tri-generation energy supply. Biomass Bioenergy 2009;33(2):223–33.
[62] Rauch P, Gronalt M. The effects of rising energy costs and transportation mode mix on forest fuel procurement costs. Biomass Bioenergy 2011;35(1):690–9.
[63] Kangas AS, Kangas J. Probability, possibility and evidence: approaches to consider risk and uncertainty in forestry decision analysis. Forest Policy and Economics 2004;6(2):169–88.
[64] Petrovic D. Simulation of supply chain behaviour and performance in an uncertain environment. Forest Policy and Economics 2001;71(1–3):429–38.
[65] Ells A, Bulte E, van Kooten GC. Uncertainty and forest land use allocation in British Columbia: vague priorities and imprecise coefficients. Forensic Science 1997;43(4):509–20.
[66] Bowyer C, Baldock D, Kretschmer B, Polakova J. The GHG emissions intensity of bioenergy: Does bioenergy have a role to play in reducing GHG emissions of Europe's economy? London: Institute for European Environmental Policy (IEEP); 2012.
[67] Chrwan-JYH H. Evaluating the impact of operating environments on MRP system nervousness. International Journal of Production 1989;27(7):1115–35.
[68] British Columbia Ministry of Forests and Range. Major primary timber processing facilities in British Columbia; 2008.
[69] Carlsson D, D'Amours S, Martel A, Rönnqvist M. Supply chain planning in the pulp and paper industry. Information Systems and Operational Research 2009;47(3):167–83.
[70] Demirbas A. Fuelwood characteristics of six indigenous wood species from the Eastern Black Sea Region. Energy Sources 2003;25:309–16.
[71] Lehtikangas P. Quality properties of pelletised sawdust, logging residues and bark. Biomass Bioenergy 2001;20(5):351–60.
[72] Mccormic K. Bioenergy systems and supply chains in Europe: conditions, coordination and capacity. In: Choi TM, Cheng TCE, editors. Supply chain coordination under uncertainty. New York: Springer-Verlag; 2011 p. 545–62.
[73] Mula J, Poler R, García-Sabater JP, Lario FC. Models for production planning under uncertainty: a review. International Journal of Production Economics 2006;103(1):271–85.
[74] Petrovic D, Roy R, Petrovic R. Supply chain modelling using fuzzy sets. International Journal of Production Economics 1999;59(1–3):443–53.
[75] Birge JR, Louveaux F. Introduction to stochastic programming. New York: Springer Verlag; 1997.
[76] Shapiro JF. Challenges of strategic supply chain planning and modeling. Computers & Chemical Engineering 2004;28(6–7):855–61.
[77] Benders JF. Partitioning procedures for solving mixed-variables programming problems. Numerische Mathematik 1962;4(1):238–52.
[78] Bertsimas D, Sim M. Robust discrete optimization and network flows. Mathematical Programming 2003;98(1):49–71.
[79] Kim J, Realff MJ, Lee JH, Whittaker C, Furtner L. Design of biomass processing network for biofuel production using an MILP model. Biomass Bioenergy 2011;35(2):853–71.
[80] Kim J, Realff MJ, Lee JH. Optimal design and global sensitivity analysis of biomass supply chain networks for biofuels under uncertainty. Computers & Chemical Engineering 2011;35(9):1738–51.
[81] Svensson E, Strömberg A, Patriksson M. A model for optimization of process integration investments under uncertainty. Energy 2011;36(5):2733–46.
[82] Svensson E, Berntsson T. Planning future investments in emerging energy technologies for pulp mills considering different scenarios for their investment cost development. Energy 2011;36(11):6508–19.
[83] Chen C, Fan Y. Bioethanol supply chain system planning under supply and demand uncertainties. Transportation Research Part E: Logistics and Transportation Review 2012;48(1):150–64.
[84] Tay DHS, Ng DKS, Tan RR. Robust optimization approach for synthesis of integrated biorefineries with supply and demand uncertainties. Environmental Progress and Sustainable Energy 2012, published online, doi:10.1002/ep.10632.